ONLINE ISSN 2069-7430
ISSN-L 1841-4737
PRO LIGNO
www.proligno.ro
Vol. 21 N° 4 2025
pp. 3-14

ARTIFICIAL INTELLIGENCE AND CIRCULAR ECONOMY IN WOOD CONSTRUCTION: EXPLORING AI's ROLE IN ENHANCING SUSTAINABILITY AND MATERIAL REUSE

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Abstract:

Multi-story wood construction offers sustainability potential, but regulatory, material traceability, and economic challenges limit circular economy (CE) adoption. At the same time, Artificial Intelligence (AI) is emerging as a transformative tool that can optimize construction processes and possibly act as an enabler for change. However, the extent to which AI can leverage CE in wood construction is still underexplored.

This study conducts a descriptive analysis *to examine trends in the wood construction industry and stakeholder perspectives on AI's role in facilitating CE adoption within wood construction. By engaging key market actors, the research explores how AI-driven technologies such as digital twins, machine learning, and material tracking can address regulatory barriers, improve resource efficiency, and thereby enhance CE goals. The survey results indicate that tools for material traceability and design optimization are already in use by a majority of stakeholders and are perceived as impactful for CE, whereas advanced AI applications (e.g.* AI-driven structural health monitoring*) remain underutilized. Notably, researchers and technology providers express higher confidence in AI's CE potential than construction firms, pointing to awareness and implementation gaps. These insights highlight AI's critical enabling role, particularly through digital transparency and data-driven decision-making, in advancing circular practices in wood construction.*

Key words: *wooden construction industry; circular economy; new technologies; sustainability: artificial intelligence.*

INTRODUCTION

The construction industry is among the most resource-intensive sectors globally, consuming approximately 50% of all raw materials and generating nearly one-third of total waste (European Commission 2023a, UNEP 2023a). Buildings and construction activities account for approximately 37% of global CO_2 emissions (UNEP, 2023b), contributing significantly to environmental degradation and climate change. In response, sustainability initiatives such as the CE frameworks have been introduced to improve material efficiency, reduce waste, and promote sustainable practices (Adams *et al.* 2017). The OECD (2023) emphasizes the critical role of resource efficiency in enabling CE transitions, highlighting how improved material tracking and reuse can enhance sustainability outcomes in the construction industry. However, despite these frameworks, the construction industry still struggles with fragmented data, regulatory inconsistencies, and lack of standardized approaches (Keles *et al.* 2025).

Wood construction, particularly for multi-story buildings, holds significant promise for CE implementation due to timber's renewable nature, carbon sequestration capacity, and lower embodied energy compared to steel or concrete (Hegeir *et al.* 2022). However, current practices fall short of this potential, for instance, only about 30% of timber recovered from demolitions is actually reused (the rest is downcycled or landfilled) due to inadequate tracking, fragmented regulations (European Commission 2023a, Pathan *et al.* 2023), and inefficient lifecycle management. This lack of integrated data and oversight makes it difficult for firms to meet evolving CE benchmarks (Keles *et al.* 2025). Artificial intelligence (AI) has emerged as a transformative enabler to tackle these challenges in wood construction, by optimizing material flows, providing predictive analytics for sustainability, and ensuring regulatory compliance through advanced monitoring systems (Himeur *et al.* 2023, Ucar *et al.* 2024). In particular, AI-driven tools like digital twins can create virtual replicas of buildings to simulate material performance and resource efficiency in real-time, enabling adjustments that minimize waste and extend material lifecycles (Pathan *et al.* 2023). Similarly, machine learning and predictive maintenance tools can improve decision-making in material reuse, enhance long-term material traceability,

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and support compliance with sustainability standards. Without real-time, data-driven systems like these, construction firms struggle to align with broader sustainability targets such as the United Nations Sustainable Development Goals and the European Green Deal (UNEP 2023a; European Commission 2023b).

Current digital solutions, such as Building Information Modeling (BIM) and material passports, have improved documentation but remain limited in ensuring real-time material traceability and predictive reuse modelling. AI has the potential to bridge these gaps by enabling dynamic tracking, optimizing resource flows, and enhancing decision-making for CE adoption in wood construction (Bertin *et al.* 2020).

OBJECTIVE

Recent studies have demonstrated that the integration of AI and CE offers significant potential for enhancing sustainability and resource efficiency (Singh 2023). Despite growing interest in AI, its role in advancing CE practices in sustainable construction remains underexplored. Most prior studies on AI in CE contexts have focused on manufacturing and logistics. There is a current knowledge gap regarding how AI-driven circular strategies, especially examined from a multi-stakeholder perspective, can facilitate CE in the construction industry. This study addresses that gap by integrating the Resource-Based View (RBV) framework by analyzing the perspectives of key stakeholders on AI applications for CE in wood construction, thereby providing initial empirical insights into AI's opportunities and challenges in this context. This study addresses that gap.

To address these challenges and contribute to the development of AI-driven CE models in the wood construction industry, this study explores the following research questions:

1. How is AI currently applied within the construction industry to support CE practices, particularly in wood construction?
2. What are the key stakeholders' perspectives on the role of AI in enabling CE adoption in wood construction?
3. Which factors influence the implementation of AI-driven CE solutions in the wood construction industry?

By answering these questions, this research aims to provide valuable insights that can accelerate the adoption of AI in the construction industry. Accordingly, this study aims to: (1) identify how AI technologies are currently applied to support circular practices in wood construction; (2) compare key stakeholder groups' perspectives on AI's role in enabling circularity; and (3) indicate factors that facilitate or hinder implementation of AI-driven circular solutions in the wood construction industry.

THEORETICAL FRAMEWORK

Given the identified challenges in CE adoption for wood construction, such as inefficient material tracking, regulatory fragmentation, and lack of digital integration, AI emerges as a strategic resource that can address these issues through enhanced decision-making, predictive analytics, and automated lifecycle management. According to the RBV of the firm (Barney 1991, Hart 1995), organizations gain sustainable competitive advantages by effectively deploying valuable, rare, inimitable, and non-substitutable resources. We apply this theoretical lens to AI-driven CE practices in wood construction, leveraging AI innovations as strategic resources can enhance firms' resource efficiency and sustainability, ultimately providing a competitive edge in the industry. This framework highlights the potential for AI to transform traditional construction methods, fostering innovation and long-term advantages in the industry. The integration of AI with CE principles represents a transformative approach in the construction industry (Hegeir *et al.* 2022).

Application of AI in CE in the Wood Construction Industry

Given the increasing popularity of mass timber construction, engineered wood products such as cross-laminated timber and glue-laminated timber require precise tracking and efficient reuse strategies to fully align with CE principles. The principles of the CE, along with their corresponding AI applications, potential impacts, and implementation statuses, are compiled in Table 1.

Table 1

AI-Driven Circular Economy Integration in Wood Construction

CE Principle	AI Application	Potential Impact	Status	References
Material Reuse	AI-driven sorting and identification of reclaimed wood	Enhanced recovery and reuse of timber components	Emerging technology, limited large-scale implementation	Sofiat *et al.* 2021
Waste Reduction	Predictive modelling for wood waste generation in prefabrication	Optimized raw material utilization, minimized offcuts	Conceptual stage, limited practical applications	Tezel *et al.* 2020
Resource Efficiency	AI-optimized design for modular timber construction	Improved material utilization, energy efficiency, lower embodied carbon	Growing adoption in industrialized construction	Ellen MacArthur Foundation, 2019
Lifecycle Management	Digital twins for real-time tracking of timber elements in buildings	Extended lifespan of wooden components through proactive maintenance	Growing adoption in large-scale wood projects	Singh, 2023
Supply Chain Optimization	Blockchain-enabled verification of sustainable wood sourcing	Increased transparency in timber certification and provenance tracking	Pilot projects and proof-of-concept stages	Abdullahi *et al.* 2024

The sustainability impact of AI-enabled circular construction manifests across environmental, economic, and social dimensions. Environmental benefits include reduced waste and improved resource efficiency, though ensuring net positive environmental impact of AI systems remains a challenge (Ellen MacArthur Foundation 2019). Economic advantages encompass cost savings through optimized processes and new business models, despite high initial implementation costs. Social impacts include enhanced safety and improved working conditions, balanced against concerns about job displacement and the need for re-skilling (Baduge 2022).

While BIM and sensor networks are frequently highlighted in literature as enablers of circular construction (Pathan *et al.* 2023, Keles *et al.* 2025), actual implementation in the wood sector remains sparse. Across stakeholder groups, a recurring barrier is the limited digital competence necessary to adopt AI tools, suggesting that human capital development is a precondition for AI-led CE innovation (Sofiat *et al.* 2021, Singh 2023).

Stakeholder Adoption and Implementation Challenges

Given the differing priorities, technical competencies, and institutional constraints of these stakeholder groups, their perceptions of AI's utility and readiness for circular construction are likely to vary considerably. Understanding these differences is critical for designing inclusive CE strategies that align with the capabilities and expectations of each group. This divergence provides a strong rationale for conducting a multi-stakeholder survey to capture nuanced perspectives on AI adoption across the wood construction value chain. Implementation of AI-driven CE solutions in the wood construction industry necessitates collaboration among various stakeholders. Each group, ranging from construction firms and policymakers to technology developers and researchers, faces distinct adoption factors, challenges, and opportunities in integrating AI into circular wood construction, as discussed by Mankar *et al.* (2023) and others. These challenges necessitate targeted solutions, including digital skills training and the development of AI-specific regulations for CE (Singh 2023), as outlined in Table 2.

Table 2

Stakeholder Adoption and Implementation Challenges

Stakeholder Group	Adoption Factors	Implementation Challenges	Potential Solutions	References
Construction Firms	Awareness of AI-CE benefits for wood materials	Resistance to change, lack of digital skills	Educational initiatives, digital training, real-world case studies of AI in wood reuse	Mankar *et al.* 2023

Architects	Interest in sustainable and circular design enabled by AI tools (e.g. digital twins, generative design)	Limited access to AI-integrated design platforms, lack of CE performance data for materials	Collaborative design platforms, training in AI-enhanced CE tools, access to CE material traceability databases	Bertin *et al.* 2020, Atta and Talib 2023
Technology Developers	System integration for AI-enhanced wood lifecycle tracking	Complexity of implementation in fragmented supply chains	Industry collaboration, incentives for AI-enabled digital wood twins	Sofiat *et al.* 2021
Researchers & Policymakers	Identifying AI applications for circular wood construction. Regulatory alignment with CE goals for timber buildings	Limited empirical data on AI-driven timber reuse. Lack of standardized frameworks for AI-driven CE	Focused studies on AI-CE impact for timber buildings. Development of AI-specific CE regulations, harmonized certification for AI-assisted wood tracking	Singh 2023 and Abdullahi *et al.* 2024

The interface between technology and policy plays a crucial role in facilitating the transition toward more sustainable construction practices, particularly in addressing challenges related to material traceability and regulatory compliance (Singh 2023).

Stakeholder Adoption and Implementation Challenges Arranged According to RBV Element

The RBV framework provides a strategic perspective on how AI-driven CE solutions in the wood construction industry can create sustainable competitive advantages. In alignment with RBV, AI capabilities can be classified as valuable, rare, inimitable, and non-substitutable (VRIN) resources. These classifications underpin competitive advantage in organizations. For instance, AI systems enabling real-time traceability of reclaimed timber exemplify valuable resources, while proprietary predictive models for disassembly logistics may constitute rare or inimitable capabilities. Below, examples of AI applications in wood construction to these VRIN categories are mapped out (Table 3), to illustrate how AI can serve as a strategic resource.

Valuable Resources

- Technological Capabilities: AI-driven digital twins, machine learning for predicting wood degradation, and IoT-enabled monitoring systems enhance decision-making and material efficiency in timber buildings (Singh 2023).
- Knowledge Resources: Educational initiatives and digital skills training improve understanding of AI's role in optimizing the reuse of engineered wood products and conventional timber components (Mankar *et al.* 2023).

Rare Resources

- Specialized Applications: AI-driven identification systems for salvaging high-quality wood and predictive analytics for moisture control in wooden structures (Sofiat *et al.* 2021).
- Technical Integration Capabilities: Combining AI with sensor-based monitoring for fire safety and material integrity assessments in timber buildings (Tezel *et al.* 2020).

Inimitable Resources

- Process Innovations: AI-assisted deconstruction of wooden buildings and AI-driven structural health monitoring (Singh 2023).

Organizational Learning: Industry-wide adoption of AI-driven CE practices for wood through knowledge-sharing platforms and standardization efforts (Charef *et al.* 2021).

Non-Substitutable Resources

- Digital Transformation Advantages: AI-powered tracking of embodied carbon in wood materials, ensuring compliance with CE policies (Ellen MacArthur Foundation 2019, Mankar *et al.* 2023).
- Sustainable Practice Integration: AI-enabled optimization of forest-to-construction supply chains for improved circularity (Ellen MacArthur Foundation 2019).

Table 3

AI enabled competitive advantage within the wood building industry

RBV Element	AI Resource	Competitive Advantage	References
Valuable	Digital twins, machine learning, IoT	Enhanced decision-making, efficiency, maintenance	Singh 2023
Rare	AI-driven material reuse, predictive waste modelling	Improved circular economy alignment, reduced waste	Sofiat *et al.* 2021
Inimitable	AI-optimized design, digital twins for lifecycle tracking	Unique sustainability advantages, regulatory compliance	Tezel *et al.* 2020
Non-Substitutable	AI-driven supply chain tracking, predictive analytics	Increased transparency, industry-wide CE integration	Ellen MacArthur Foundation 2019

These AI resources address the key challenges i.e., AI-powered material tracking (non-substitutable) resolves traceability issues; predictive analytics (valuable) improves lifecycle monitoring; and AI-driven regulatory compliance tools (rare) enhance policy alignment. These strategic advantages are crucial for accelerating CE adoption in wood construction.

These theoretical insights shaped the focus of our survey instrument, ensuring that the questions posed to stakeholders align with recognized CE principles, AI applications, and RBV resource categories identified in literature (see Appendix 1 for the survey items aligned with Table 1 and 3 topics).

METHODOLOGY

We employed a structured questionnaire survey design (i.e. a purely quantitative descriptive approach). The questionnaire included an initial section of background items to categorize respondents into the four stakeholder groups, followed by 37 Likert-scale statements (1 = “do not agree” to 10 = “totally agree”) about AI and circular economy topics (see Appendix 1 for the full list of statements). Each statement was pre-mapped to one of the four RBV dimensions (Valuable, Rare, Inimitable, Non-substitutable). For analysis, we calculated an average score for each RBV dimension per respondent, i.e. we averaged the ratings of all statements associated with that RBV category for each individual. We then computed the mean of these scores for each stakeholder group, yielding group-level perceptions of the importance of each RBV-category capability.

The survey was distributed via targeted professional networks, across four stakeholder categories: 13 architects, 21 construction firms, 14 technology developers, and 13 researchers and policymakers or research professionals (includes academic researchers and government or industry policy professionals). The survey was distributed digitally via professional networks and institutional mailing lists in Sweden between March and April 2025. Although the response rate (≈20%) and absolute sample size (N=61) limit generalizability, the sample encompasses a range of key stakeholders, providing initial insights across the spectrum of industry perspectives. These aggregated scores were compared across groups. This mapping enabled analysis of perceptions across strategic resource categories, which was visualized through the distribution of scores in figures to identify highest- and lowest-rated items (Figures 1-3). Also, we did not perform inferential statistical tests due to the exploratory scope and sample size, instead, we focused on descriptive patterns and differences in mean scores. This sampling approach was chosen to capture a comprehensive landscape of AI adoption (Sofiat *et al.* 2021) while allowing nuanced comparisons across stakeholder types (Na *et al.* 2023).

The use of a theory-grounded Likert scale enhances the validity of our findings, as such alignment between theoretical constructs and survey items strengthens the measurement of abstract concepts (Wei *et al.* 2024). By disseminating the questionnaire through multiple industry channels, we obtained a diverse and comprehensive sample of the wood construction sector, ensuring that the findings indicate the current state of AI adoption while also highlighting areas for future research (Sofiat *et al.* 2021, Na *et al.* 2023).

RESULTS AND DISCUSSION

The results reveal a clear hierarchy of perceived AI capability and maturity across the RBV categories. As shown in Figure 1 and Table 4, non-substitutable resources, such as AI enabled traceability, digital supply chain modeling, and AI-supported lifecycle integration, received the highest ratings (mean = 6.93 for researchers; 6.13 for architects). These applications are seen as foundational to CE-aligned transparency and integration, consistent with prior work by Ellen MacArthur Foundation (2019) and Mankar *et al.* (2023).

Rare resources, including AI-powered reuse classification and predictive maintenance systems, also scored highly (mean ≈ 6.6), particularly among technology developers and researchers. These findings align with studies emphasizing AI’s role in lifecycle optimization (Singh 2023; Abdullahi *et al.* 2024).

Table 4

Mean Scores of AI Capabilities by RBV Dimension and Stakeholder Group

	Architects	Construction Firms	Researchers & Policymakers	Technology Developers
Inimitable	4.31	4.08	4.54	4.54
Non-substitutable	6.13	5.69	6.93	6.93
Rare	6.03	5.60	6.68	6.68
Valuable	4.43	3.91	4.33	4.33

In contrast, inimitable and valuable AI resources, such as structural health monitoring, advanced lifecycle simulations, and internal digital competencies, received notably lower ratings (mean ≈ 4.0–4.5), particularly from construction firms. These patterns suggest that while high-level digital infrastructure is conceptually recognized, actual implementation of complex or organization-specific solutions remains limited and trends suggest perceptual divergence between design and implementation actors (Tezel *et al.* 2020, Himeur *et al.* 2023).

The comparative analysis of stakeholder responses reveals distinct patterns. Researchers and technology developers consistently reported higher confidence in AI's CE-enabling potential, especially regarding rare and non-substitutable resources. This reflects greater exposure to emergent tools and conceptual solutions (Keles *et al.* 2025).

Conversely, construction firms exhibited the lowest mean ratings across all RBV categories. This suggests operational conservatism, limited AI literacy, or resource constraints, challenges echoed by Sofiat *et al.* (2021) and Charef *et al.* (2021). Architects' responses placed them between these extremes, demonstrating moderate optimism particularly toward valuable digital infrastructure like BIM and digital twins.

These findings highlight the need for coordinated implementation strategies and knowledge transfer across stakeholder groups to bridge perception gaps and foster collaborative innovation (Pathan *et al.* 2023).

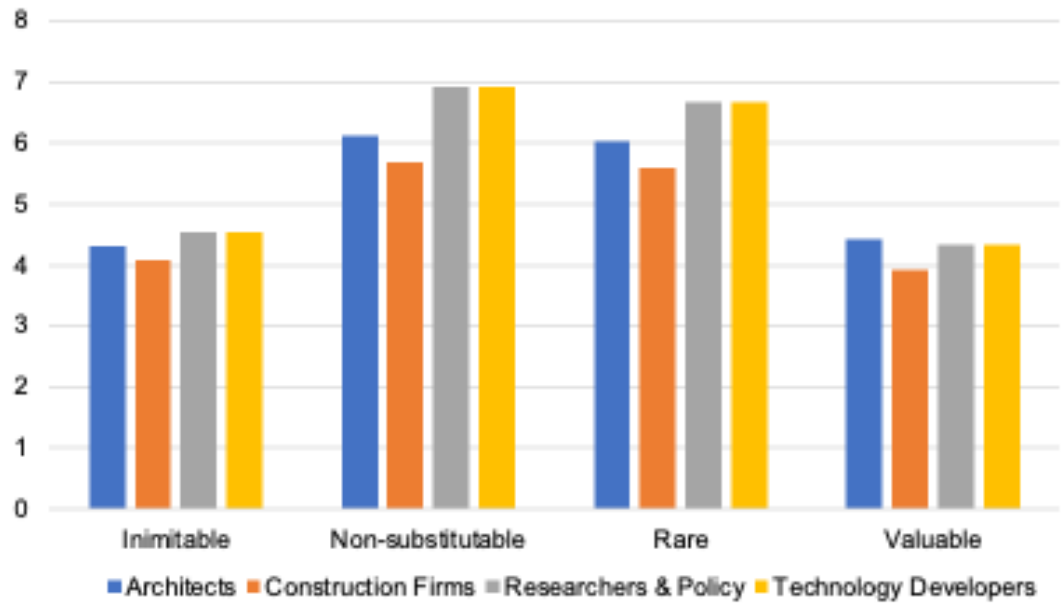

Fig. 1.
Perceived Maturity of AI Capabilities by RBV Dimension and Stakeholder Group.

Despite the growing maturity of select AI tools, the survey revealed clear gaps in stakeholder confidence regarding more advanced capabilities. These include AI used to support reuse, AI-driven structural health monitoring, and predictive models for wood degradation and lifecycle extension, all of which received the lowest average ratings across all groups, particularly among construction firms (see Figure 2). These capabilities typically require high digital-physical integration, specialized data infrastructure, and regulatory flexibility, making them difficult to scale in practice.

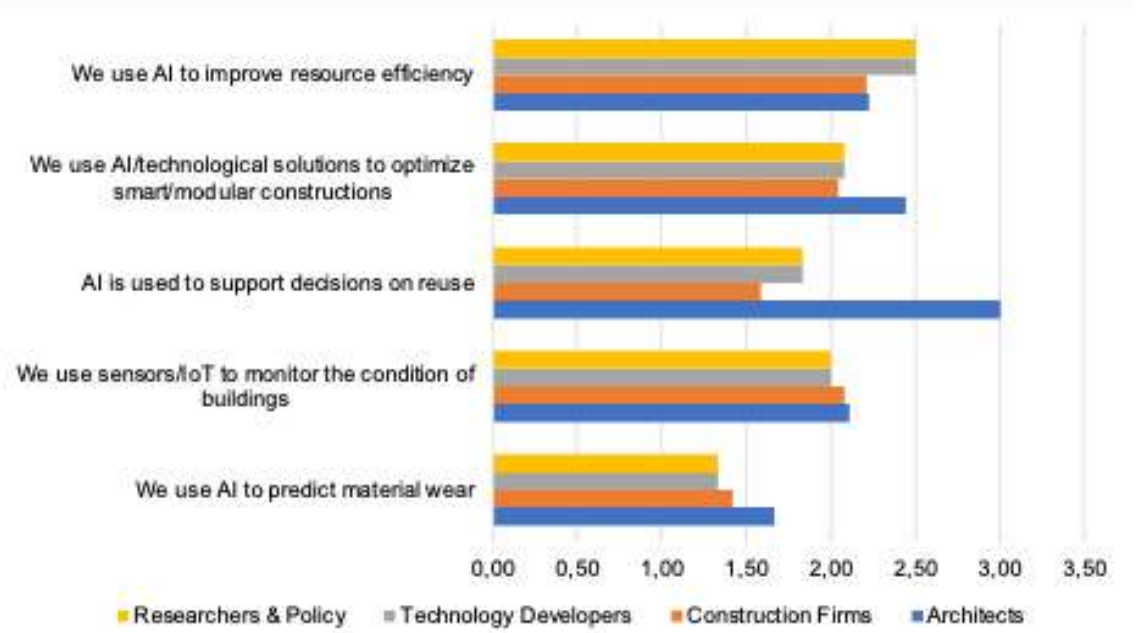

Fig. 2.
Lowest Rated AI Capabilities by Stakeholder Group.

Most of these items fall within the inimitable and valuable RBV dimensions, suggesting that while they offer long-term strategic advantage, they remain constrained by feasibility and familiarity. Even researchers and technology developers, though slightly more optimistic, showed only moderate support. As highlighted by Sofiat *et al.* (2021) and Tezel *et al.* (2020), this gap underscores the need for demonstrator projects, industry standards, and digital up-skilling to reduce perceived risk and accelerate adoption. Without such efforts, these high-potential tools risk remaining conceptually promising but practically sidelined. This pattern correlates with the RBV, i.e. resources that are valuable but not yet common are harder for firms to implement, whereas those that have become industry standards see broader acceptance.

The survey results highlight a clear consensus around a set of AI applications perceived as impactful for CE integration in wood construction. The top five rated AI capabilities across all stakeholders were (Figure 3), digital twins for material tracking, predictive analytics for resource efficiency, enabler for fulfilling future environmental requirement, AI-optimized modular design, and CE-focused supply chain modeling. Notably, these tools mostly fall into the Non-substitutable or Rare RBV categories and align closely with digital infrastructures already familiar to practitioners, such as BIM and lifecycle management systems, which likely explains their higher acceptance. Researchers and technology developers rated these highest (mean ≈ 7.5–8.5), with relatively strong support also observed among architects and construction firms.

This convergence indicates that AI tools enabling transparency, traceability, and systems-level optimization are no longer viewed as speculative, but rather as practical enablers of circularity, in line with recent findings by Singh (2023), Bertin *et al.* (2020), and Ellen MacArthur Foundation (2019). These high-confidence areas offer a clear starting point for CE-aligned digitalization strategies in the wood construction industry.

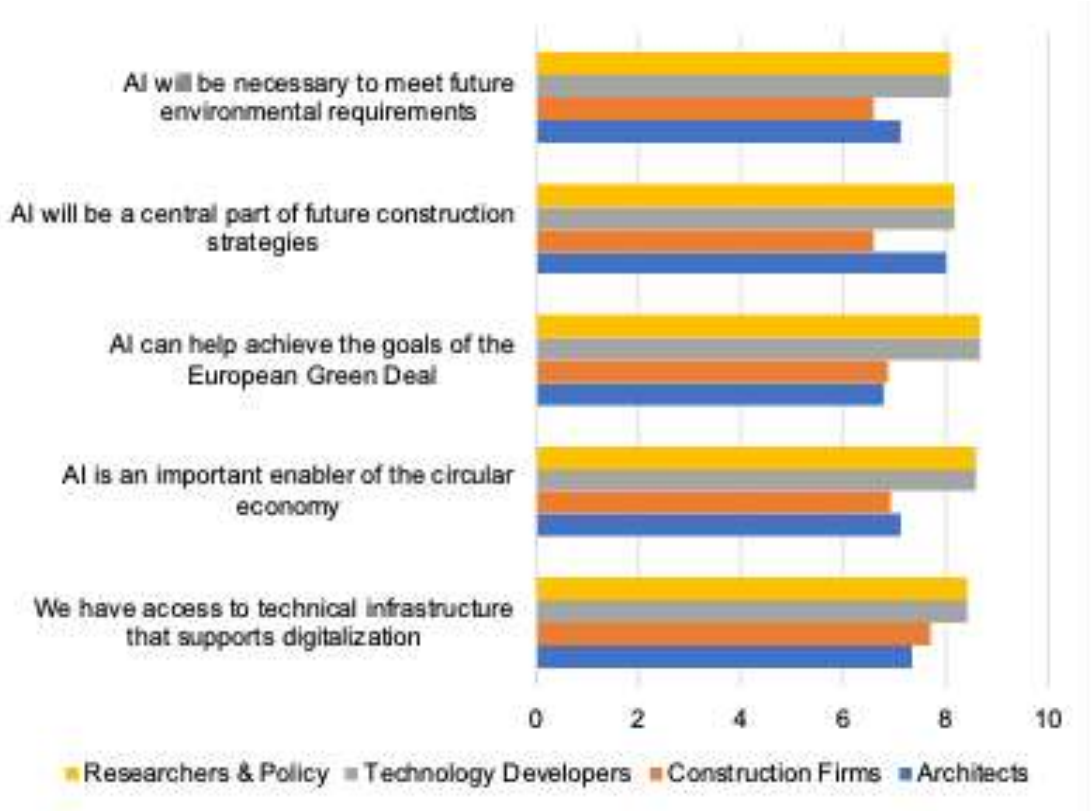

Fig. 3.
Highest Rated AI Capabilities by Stakeholder Group.

The RBV lens provides strategic insight into how stakeholders perceive AI as a source of sustainable advantage. High-performing applications (e.g. digital traceability, supply chain modeling) are already embedded in workflows and are seen as scalable. In contrast, lower-rated capabilities are often tied to:

- Cross-actor data dependencies (e.g. inter-firm lifecycle analytics)
- Integration of AI with physical systems (e.g. AI-driven structural health monitoring)
- Policy and standardization bottlenecks (European Commission 2023b)

To overcome these barriers, sectoral strategies should include:

- Targeted up-skilling programs (in line with Mankar *et al.* 2023)
- Incentivized public-private partnerships
- Development of sector-specific standards and regulatory support (OECD 2023)

This confirms the role of RBV-informed innovation roadmaps in advancing CE in construction-where current value creation lies in practical tools, while future advantage may derive from hard-to-replicate digital-physical systems (Tezel *et al.* 2020, Charef *et al.* 2021).

In answer to RQ1, the findings indicate that AI tools for transparency and design optimization (such as digital twin tracking, BIM and AI-assisted modular design) are already being applied by more than 60% of respondents and are viewed as the most impactful for CE integration in wood construction. However, advanced applications like predictive disassembly or AI-driven structural health monitoring is underutilized, cited by fewer than 20%. Addressing RQ2, we found notable differences in stakeholder perspectives, researchers and technology developers expressed higher confidence in AI's CE-enabling potential than construction firms, suggesting gaps in awareness and readiness. Regarding RQ3, the results highlight several key factors influencing AI-driven CE implementation – notably, the need for cross-organizational data sharing, the challenges of integrating AI with physical construction processes (e.g. AI-driven structural health monitoring), and the influence of supportive policies and standards – all of which can either facilitate or hinder adoption
Summary of findings:

- Stakeholders assign the highest scores to non-substitutable AI capabilities, validating their perceived maturity and strategic relevance.
- Construction firms lag behind other groups in confidence, suggesting the need for support and engagement strategies.

- The lowest-rated capabilities reflect a lack of readiness for advanced AI in reuse, disassembly, and lifecycle prediction—mirroring barriers noted in Himeur *et al.* (2023) and Sofiat *et al.* (2021).
- Adoption is currently strongest where digital workflows align with CE needs; complex, physical-world AI applications remain aspirational.

CONCLUSIONS

This study has explored how AI is perceived by key stakeholders as a driver of CE adoption in the wood construction sector. Using the RBV as an analytical framework, the research offers a structured interpretation of how different types of AI capabilities-categorized as valuable, rare, inimitable, and non-substitutable-are evaluated in terms of maturity, strategic relevance, and implementation feasibility.

The findings suggest that AI applications perceived as non-substitutable, particularly those related to supply chain traceability, digital twins, and lifecycle integration, are viewed as the most mature and strategically aligned with CE objectives. These technologies appear to be gaining traction across the sector, especially among researchers and technology developers who recognize their capacity to improve transparency, regulatory compliance, and systemic resource optimization (Ellen MacArthur Foundation 2019, Mankar *et al.* 2023). Their relatively high ratings across stakeholder groups point to a readiness for broader deployment in practice.

By contrast, AI capabilities classified as valuable or inimitable, such AI-driven structural health monitoring, or internally developed digital competencies, were rated lower. This discrepancy underscores a gap between conceptual potential and practical implementation. In many cases, these lower scores reflect technical complexity, lack of internal infrastructure, or limited exposure among practitioners, especially construction firms, who consistently reported lower confidence in AI's CE-enabling capacity. The findings align with previous studies identifying digital skill shortages and implementation barriers as persistent challenges in the built environment (Tezel *et al.* 2020, Sofiat *et al.* 2021, Himeur *et al.* 2023).

Another significant insight concerns the divergence in perceptions among stakeholder groups. Technology developers and researchers expressed considerably higher optimism about the role of AI in advancing CE, whereas practitioners, especially construction firms, showed more skepticism. This variation indicates that the maturity of AI adoption is not merely a function of technological availability but is also shaped by professional role, organizational capacity, and access to enabling conditions such as training, regulatory support, and cross-sectoral collaboration (Charef *et al.* 2021, Pathan *et al.* 2023).

Taken together, the results point to a need for coordinated efforts to enhance AI readiness in the sector. Stakeholder-specific support structures, including digital up-skilling, regulatory frameworks for data sharing and lifecycle tracking, and collaborative mechanisms for testing and validating AI tools, will be critical to accelerating adoption (OECD 2023, Mankar *et al.* 2023). While the RBV framework confirms that some AI tools are already contributing to strategic advantage in CE transitions, others remain aspirational, requiring sustained investment and broader systemic alignment.

Future research should deepen these findings by incorporating respondent-level data to enable inferential statistical analysis of adoption patterns. Longitudinal studies could further illuminate how perceptions and implementations of AI evolve over time within and across organizations. Comparative research across geographic regions and material systems would also enhance understanding of how contextual factors influence AI-CE integration.

AI, while not a universal solution, plays an essential enabling role in making circular wood construction both technically feasible and strategically viable. Realizing its full potential will depend on bridging current capability gaps, aligning stakeholder expectations, and fostering a shared commitment to innovation throughout the construction ecosystem.

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APPENDIX 1. QUESTIONNAIRE (RBV-dimensions and Average values)

	Question	RBV-dimension	Architects	Construction Firms	Technology Developers	Researchers & Policymakers
1	We have access to technical infrastructure that supports digitalization	Valuable	7.33	7.71	8.42	8.42
2	We have access to high-quality data in our construction projects	Valuable	6.56	6.71	7.25	7.25
3	Our organization has technical competence in digital systems	Valuable	7.67	6.71	7.50	7.50
4	We have invested in training on digital tools	Valuable	6.67	5.54	6.58	6.58
5	We use BIM or similar systems in construction processes	Valuable	8.22	7.63	6.92	6.92
6	We use digital twins at some stage of our projects	Valuable	4.11	4.58	5.33	5.33
7	We use sensors/IoT to monitor the condition of buildings	Valuable	2.11	2.08	2.00	2.00
8	We have tested or evaluated AI solutions	Valuable	5.44	3.88	4.67	4.67
9	We use AI/technological solutions to reduce material waste	Valuable	2.56	1.88	2.58	2.58
10	We use AI/technological solutions to optimize smart/modular constructions	Valuable	2.44	2.04	2.08	2.08
11	We use AI to predict material wear	Valuable	1.67	1.42	1.33	1.33
12	AI is used to support decisions on reuse	Valuable	3.00	1.58	1.83	1.83
13	AI is used to improve traceability of building components (digital passports)	Valuable	3.11	2.17	2.67	2.67
14	AI is integrated into our BIM system	Valuable	3.11	2.54	2.83	2.83
15	We use AI to improve resource efficiency	Valuable	2.22	2.21	2.50	2.50
16	AI improves the quality of our buildings	Valuable	3.00	2.63	3.00	3.00
17	We have a clear strategy for AI in the circular economy	Inimitable	3.11	2.25	2.33	2.33
18	AI is part of our innovation/sustainability strategy	Inimitable	3.44	3.04	3.17	3.17
19	Management supports AI investments	Inimitable	5.67	5.04	5.58	5.58
20	We have concrete plans to expand our use of AI	Inimitable	4.89	4.13	5.42	5.42

21	We collaborate with other actors on AI and the circular economy	Inimitable	2.78	3.42	4.17	4.17
22	There is built-in resistance to AI in our organization	Inimitable	6.00	6.58	6.58	6.58
23	We do not experience technical difficulties with AI integration	Valuable	5.78	5.04	5.08	5.08
24	Lack of competence is a barrier to AI implementation	Valuable	4.67	4.13	5.33	5.33
25	Our customers demand digitally traceable. sustainable products	Rare	4.56	5.75	6.25	6.25
26	AI solutions are mature enough for practical use	Rare	4.78	4.17	5.33	5.33
27	AI simplifies compliance with environmental regulations and standards	Rare	5.11	5.46	6.25	6.25
28	AI increases transparency of material origins	Rare	4.56	5.25	6.33	6.33
29	AI provides a competitive advantage in our industry	Rare	6.33	6.17	6.33	6.33
30	Clear data standards contribute to development	Non-substitutable	4.33	3.67	3.00	3.00
31	Regulations and policies support AI use in the circular economy	Non-substitutable	4.44	4.33	4.92	4.92
32	AI can help achieve the goals of the European Green Deal	Non-substitutable	6.78	6.88	8.67	8.67
33	AI is an important enabler of the circular economy	Non-substitutable	7.11	6.92	8.58	8.58
34	AI will be necessary to meet future environmental requirements	Non-substitutable	7.11	6.58	8.08	8.08
35	AI can improve the reuse of wood and other construction materials from demolition	Rare	7.00	5.79	8.33	8.33
36	Digital twins should become standard in future construction projects	Rare	7.22	5.38	7.67	7.67
37	AI will be a central part of future construction strategies	Rare	8.00	6.58	8.17	8.17